Imported Input Varieties and Product Innovation

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Imported input varieties and product innovation: evidence from five developing countries ☆

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Abstract

We examine how access to imported intermediate inputs affects firm-level product innovation in five developing counties. We combine trade data with survey data on innovation and develop a method to determine whether new inputs were essential for the product innovation. We find evidence that the number of newly imported varieties has a significant positive and sizable impact on product innovations that use new inputs and in particular innovations for which a new input is an essential feature. We provide suggestive evidence that this effect comes from access to better quality imports. Given the large expansion of the number of Chinese firms exporting the five developing countries, we also analyze the effect of firm-varieties from China on product innovation. We find evidence in favor of a positive correlation, but we cannot confidently confirm a casual relationship.

Keywords: product innovation, trade, new intermediate inputs.

JEL Classification: F1

1. Introduction

The development of innovation capacities has been central to growth in developing countries, where innovation is not just about high-technology. Even in the early stages of development learning capacities help these countries to catch up OECD (2012). Small incremental innovations that specifically address local challenges can bring important changes that improve welfare. Understanding the drivers of firm-level innovation in developing countries is thus of particular interest. A large literature has indicated a range of drivers of innovation, from the level of human capital and financial development in the economy, to the role of sound industrial policies and institutions. A

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recent strand of literature has looked at the role of trade, and in particular the role of imported intermediate inputs, in promoting product innovations.

Access to foreign intermediates may be an important determinant of firm-level innovation for a variety of reasons. First, when the imported intermediate input is not available domestically, it allows for the domestic production of better or new final products. Second, the imported inputs may be of superior quality which improves the output product's quality. Finally, foreign inputs can be cheaper or more reliable than the domestic variant, leading to lower costs. Imported intermediate inputs may therefore be of particular importance to developing countries whose domestic manufacturing industries are at early stages of development. Moreover, the definition of innovation used in this study is very broad, namely a new or significantly improved product, where new means new to the establishment and not necessarily new to the market. Because of this broad definition, the innovation rate in the sample is fairly high (48%) compared to for example European rates. A qualitative assessment of the data reveals that a significant proportion of the innovations are incremental changes to existing products, and that most of the innovations are new only to the firm.

While existing trade and growth models link the introduction of new intermediate inputs to economic growth through firm-level product innovations, the empirical literature is at best scant. A number of papers have studied the effect of intermediate input imports on productivity (Amiti and Konings (2007), Şeker (2012), Vogel and Wagner (2010)), but with the exception of one paper, there is no evidence on the link between imported inputs and innovation. In their seminal paper, Goldberg et al. (2010) find that increasing numbers of new input varieties at the industry level in India between 1989 and 1996 accounts for 31 percent of new products in that same period.

We aim to provide further empirical evidence by investigating the effect of newly imported input varieties on product innovation in five developing countries (Ghana, Tanzania, Kenya, Uganda and Bangladesh). In the baseline regression, we look at the effect of the number of input varieties imported in the firm's industry on the firm's introduction of an innovative product. In a separate regression, we interact input variety with a firm-level measure of foreign input use. We take a broad definition of product innovation that includes incremental changes to existing products and define the newness of the product in a local context. We propose a novel method to combine qualitative and quantitative survey data such that the product innovation can be classified as input-essential product innovation. We distinguish input-using innovations (that use new inputs) from input-essential innovations (for which the new input is a defining or essential feature of the innovation).

For example, one firm describes the new product as being different from the most similar product because "Now (we) use high quality copper and PVP and earlier (we) did not use improved PVP materials and copper". Another firm, making wooden doors, mentions that "Earlier (we) used low quality of local wood and now (we) are using high quality and imported wood". In these cases, the new inputs are described as an important feature of the innovation. One of the main challenges in identifying the effect of increased varieties on innovation is the potential for reverse causality and omitted variable bias. A correlation between imported inputs and innovation can in theory be driven by both "push" and "pull" factors. Access to previously unavailable inputs enables or inspires firms to use the inputs for a product innovation (push factor), whereas an innovation unrelated to international trade may increase the demand for imported inputs once the manufacturing of the new or improved product has begun (pull factor). With previously unavailable inputs we mean that one or more input varieties were initially not imported (either because there was no supply and/or there was no demand). With having access to previously unavailable inputs we thus mean that more varieties were imported, which could have been the result of push or pull events. We are interested in the push effect of increased openness to trade, and therefore want to rule out the pull factors as they represent endogeneity in this case. We pursue a number of endogeneity-robust methods. First, the concern for reverse causality is mitigated by taking the number of new input varieties prior to the product innovation. Second, we control for a range of firm-level characteristics that may drive innovation and finally we estimate an instrumental variable (IV) regression that uses data from similar countries as well as a measure of import costs based on customs delay as instrument for new input varieties.

Using a detailed Chinese firm-level export dataset, we supplement our analysis on imported product varieties from around the world with an investigation of the effect of Chinese firm-varieties. There are three reasons for doing so. First, recent studies have found a significant effect of Chinese import competition on productivity in the European Union (Bloom et al., 2016) and employment in the United States (Autor et al., 2013), but to the best of our knowledge, we are the first to study the effect of Chinese import varieties on innovation in developing countries. Second, the surge in China's exports represents a clear push factor: Chinese export growth to the world has been massive and exports to the five countries considered in this study grew even stronger. While it is plausible that China's export growth was primarily driven by a reduction in global trade barriers (Autor et al., 2013), we also adopt a method that requires weaker assumptions using a gravity model of trade. Third, in contrast to the data on world exports, the Chinese data allow us to define a variety as firm-product pair, instead of a product-country pair. This firm-product definition of a variety is closer to the new trade literature following Krugman (1979). Despite these benefits, we include first a section on world-wide imports, because even though the internal validity of the results may be higher in the Chinese case, the external validity may be lower as Chinese exports represent a non-random subset of world exports. Specifically, Chinese imports may be of lower quality (Schott, 2008), but at the same time, they may be of more similar quality and therefore more suitable to the firms in developing countries.

We find that the number of new varieties of intermediate inputs has a significant positive and sizable impact on input-using product innovation. We support this finding by establishing a link between imported varieties and innovations for which new inputs are an essential feature. These results are robust to controlling for the number of new varieties at the output level, which may induce an import competition effect, as well as to instrumental variable estimations. We show suggestive evidence that this effect comes from access to better quality imports. We find no robust evidence in favor of a firm-variety channel coming from China.

These insight can be used to inform innovation policy, but may also inform future micro-level innovation surveys. As opposed to for example the role of finance, information and markets, the role of intermediate inputs has not received sufficient attention in the WS Enterprise Survey (including the Innovation module), Community Innovation Survey (CIS) and similar firm-level innovation surveys.

The remainder of the paper is organized as follows. Section 2 provides a brief overview of the current literature on varieties, imports and innovation. In Section 3 we introduce the data and highlight the importance of new varieties, and in Section 4 we put forward the empirical model. In Section 5 and 6 we report the main results and Section 7 concludes.

2. Literature

There is a large and growing empirical literature on imported inputs and firm-level outcomes, both in developing and developed economies. Recent studies document that lower tariffs on imported inputs raise the productivity of firms in Brazil (Schor, 2004), Indonesia (Amiti and Konings, 2007), and India (Topalova and Khandelwal, 2011). Halpern et al. (2015) show that imported inputs account for 22% of productivity growth in Hungary from 1992-2003, and that this effect is equally driven by the higher quality of imported goods and by the higher number of imported varieties, which are imperfect substitutes for domestic inputs. Another strand of the literature explores the effect of imported intermediate goods on firms' export scope (Bas, 2012; Bas and Strauss-Kahn, 2014; Aristei et al., 2013) and export quality (Fan et al., 2015).

Our paper is mostly related to the influential work by Goldberg et al. (2009, 2010). Their approach is based on Romer (1994), who shows that increasing openness leads to an expansion in the number of available product varieties, thereby raising welfare. While the (static) productivity gains from increased import varieties are well-documented (e.g. Broda and Weinstein (2006), Feenstra (1994)), evidence on the dynamic gains in the form of new domestic varieties (or product innovations) is scant at best. Exploiting exogenous variation in trade liberalization in India between 1989 and 1996, Goldberg et al. (2010) show that access to new input varieties from abroad increases the domestic product scope, defined as the number of products produced by a firm. In a related study, Colantone and Crinò (2014) show that in 25 European countries, a higher share of newly imported varieties in an industry raises the share of new domestic products in that industry. The effects appear to work through both a wider as well as a better set of intermediate inputs, and the new domestic products are an important source of growth. Our paper differs from these studies in three ways. First, we use a broader measure of product innovation which includes both new and significantly improved products, thereby capturing an additional margin. Goldberg et al. (2010) count the number of products of a firm, and can therefore not identify whether a new product replaces an old one. Colantone and Crinò (2014) on the other hand identify new products as those that are in a different 8-digit category as the previous ones. Second, using qualitative survey data, we develop a novel measure of the importance of new inputs for a firm's innovation, and show that the effect of imported inputs on innovation is strongest for such input-essential innovations. To our knowledge, we are the first to use qualitative data on innovation in this context. Third, we conduct our analysis for a cross-section of poor countries, giving a broader scope to our analysis. Finally, we provide suggestive evidence of a quality channel by using firm-level data on reasons for using foreign inputs from a novel World Bank survey.

We also relate to the empirical literature on trade and innovation in developing countries using data from firm-level surveys. These surveys are typically designed to measure innovation and generally include questions on product and process innovation, and spending on R&D[1]. These surveys also collect information on a range of other firm characteristics such as employment, sales, age, or export

[1] These questions are typically of the sort: 'During the last three years, did the firm improve introduce a new product?', and 'During the last three years, did the firm conduct R&D?'.

and import behavior[2]. While panel data is uncommon, these surveys often contain some retrospective questions such that information on multiple years may be available. Using innovation survey data to study the relationship between trade and innovation is not new. Alvarez and Robertson (2004) use Chilean plant-level data from the First Survey of Technological Innovation and Mexican plant-level data from the National Survey of Employment, Salaries, Technology, and Training in the Manufacturing Sector. The authors find that exposure to foreign markets is positively correlated with product innovation, R&D and the use of new tools. Şeker (2012) uses data from the World Bank Enterprise Survey from firms in 43 developing countries between 2002 and 2006 to estimate the effect of trade orientation (exporter, importer or both) on innovation, employment, sales and labor productivity. His analysis, however, lacks a strong instrument and can only rely on firm-level controls correlated with both trade orientation and firm innovation for identification[3]. Almeida and Fernandes (2008) focus on the specific technology transfer channel that may affect innovation and find that process innovation (a new way in which the main product of the firm is produced) is related to a set of openness indicators. We differ from these studies by combining firm-level data from the World Bank Enterprise Survey, the subsequent World Bank Innovation Survey and product-level import data from UN Comtrade. Specifically, the Innovation Survey allows us to use novel qualitative information on innovations and substantially refine our data.

Finally, we relate to the literature using the dramatic increase in Chinese exports over the last three decades as a shock to its trade partners. Chinese trade growth has been shown to have wide economic implications, from increasing unemployment in the US and Europe (Autor et al., 2013; Bloom et al., 2016), to spurring technical change and reallocation of employment towards more innovative European firms (Bloom et al., 2016). Schott (2008) argues that developed countries compete with China by moving up the quality ladder. By assuming that observed differences in prices reflect differences in quality, he concludes that Chinese exports are of a lower quality than those from developed countries, a finding that is supported by Kneller and Yu (2008). To investigate the role of imports of Chinese varieties on product innovation, we use data on the number of Chinese firms exporting to the countries in our sample. To our knowledge, we are the first to use customs data at the firm level to measure import varieties, allowing us to stick much closer to the traditional

[2]Sometimes this data is collected in a separate survey, but administered to the same set of a firms so that the information can be linked by a firm id number. This is for example the case with the World Bank Enterprise Survey and the follow-up Innovation Module and Innovation Capabilities Module.

[3]Although the World Bank surveys are administered to a panel, it only accounts for a very small subset of all firms, rendering a fixed effect estimation problematic.

definition of varieties in the theoretical international trade literature.

3. Data

3.1. Firm-level data

Our firm-level data comes from the Enterprise Survey (ES) of the World Bank, which covers a wide range of business-related topics and has been administered to 130,000 firms in 135 countries since 2002. The ES has two extra modules: the Innovation Follow-up Survey (IS) and Innovation Capabilities Survey (IC). The latter two follow-up surveys were administered on a subsample of the ES firms and cover the same time-span such that the information can be merged meaningfully. At the moment, the IC module has been administered to five countries (Bangladesh, Ghana, Kenya, Uganda and Tanzania) in the latest round in 2012/2013, which covers information on the financial years 2009/2010-2011/2012. Our sample contains 1898 firms, covering 105 industries (four-digit ISIC). While the ES contains mostly quantitative questions, the IS and IC surveys contain open-ended questions, in specific to describe the firm's main innovative product. As detailed in Section 4.2, this information is key to our novel and more precise measure of firm-level innovation. For these firms, the four-digit ISIC industry is recorded.

3.2. Imports and imported varieties

Product-level import data is obtained from the United Nations Commodity Trade Database (UN Comtrade). This database provides annual product-level (HS six-digit) information on trade flows between any country pair. We use the data as reported by importers on the value (in current dollars) of imports of each product.

3.2.1. Varieties as product-country pairs

We define a 'variety' as a six-digit HS commodity - (origin) country combination in a given year for a given importing country, while we refer to a six-digit HS commodity as a 'product'. In other words, if a country imports a product from four different countries, we say that it imports four varieties of that product. Table 1 below summarizes the total number of varieties per importing country per year, over the period 2005-2013.

To gauge the importance of new imported varieties against a mere expansion of import volumes, we decompose total import growth between 2007 and 2009 - two years before the start of the firm's innovation period - into an intensive margin (existing product varieties), an extensive product margin (completely new products) and an extensive variety margin (new varieties of the same product). Table 2 reports the growth share of these three categories (they thus add up to one).

Table 1: Total number of varieties (HS6 - origin country) per year

Country	2005	2006	2007	2008	2009	2010	2011	2012	2013	% growth*
Bangladesh	36117	33904	33915	35755	35413	37081	38342	.	.	6.16
Ghana	45637	46612	50005	48042	52946	47161	53916	54313	53520	17.27
Kenya	39396	37719	37867	36654	39277	44888	.	.	49153	24.77
Uganda	26075	26218	27921	29600	31320	32486	32381	33595	32290	23.84
Tanzania	37479	37209	36206	39530	41321	41883	47285	47939	47544	26.86

*The growth rate is the total growth over the period 2005-2013, except for Bangladesh where growth is computed over the period 2005-2011 due to missing data in 2012 and 2013.

Table 2: Share of growth (2007-2009) due to intensive and extensive margin

	Bangladesh	Ethiopia	Ghana	Kenya	Uganda	Tanzania
(1) Intensive margin	0.80	0.76	1.06	0.80	0.70	0.43
(2) Product ext. margin	-0.03	-0.008	-0.04	-0.06	0.002	-0.009
(3) Variety ext. margin	0.23	0.25	-0.02	0.26	0.30	0.58

Table decomposes total import growth into the extensive and intensive margins between 2007 and 2009. Intensive margin is the contribution to growth due to importing more of already existing varieties, product extensive margin is gives the share of total growth due to importing completely new products and the variety extensive margin is the share due to importing a product from a new source country. Values are in constant US dollar and are deflated using US wholesale price indices.

Comparing the intensive and extensive margins, in all countries except Tanzania, import growth is largely driven by importing more of already existing varieties (the intensive margin). This is quite different from Goldberg et al. (2009, 2010) who find that about 35% of the growth is due to existing varieties, and that most growth (65%) is due to new products. Given that they considered a period in which India opened up significantly, this may not be so surprising. While there is no or even slightly negative growth in the product extensive margin in our sample, there is - with the exception of Ghana - considerable variety extensive margin. Thus over this period, more varieties of already existing products became available to the local economies. This means that a product was already imported from at least one country, and is now being imported from more countries.

3.2.2. Chinese varieties defined at the firm-level

We use Chinese firm-level export transaction data from the Chinese Customs Trade Statistics (CCTS) Database compiled by the General Administration of Customs of China, where we exclude non-production firms and middlemen companies. This dataset records exports of Chinese firms to all countries in detailed (HS 8-digit) product categories[4]. When concentrating on China, we define the number of imported varieties of a product in a country as the number of Chinese firms selling

[4]We use the most detailed data available, which in the case for the Chinese Customs data is eight-digit, whereas the Comtrade data is only available at the six-digit level.

that product in the country. In contrast to the "Armington" definition of varieties that we use in the rest of the analysis, using a firm as the definition of a variety is closer to the new trade literature following Krugman (1979).

4. Empirical strategy

4.1. Regression equations

We estimate the following cross-section regression:

$$INN_{ijc} = \beta_0 + \beta_1 \ln(NIV_{jc}) + \beta_2 IMG_{jc} + X_{ijc}\gamma + \varepsilon_{ijc}, \tag{1}$$

where the dependent variable is product innovation (INN) between 2009 and 2013 by firm i, in four-digit ISIC industry j in country c. We describe below in greater details the different measures of innovation that we use. The main variables of interest are the log of new input varieties (NIV) in 2009 and the log change in the value of input imports by the industry (IMG) as defined below. X_{ijc} is a basic set of controls including dummies for foreign-ownership and government-ownership, and age of the firm, and country and industry dummies.

In a separate regression, we interact input variety with a firm-level measure of foreign input use, denoted by FI, which is the share of foreign inputs to total inputs:

$$\begin{aligned} INN_{ijc} = & \quad \beta_0 + \beta_1 \ln(NIV_{jc}) + \beta_2 FI_i + \beta_3 (\ln(NIV_{jc}) * FI_i) + \\ + & \quad \beta_4 IMG_{jc} + X_{ijc}\delta + \epsilon_{ijc}. \end{aligned} \tag{2}$$

4.2. Defining product innovation

We use three ways to measure product innovation at the firm-level. The first measure is product innovation ("*Innovation*"), a dummy variable that equals one if the firm introduced any innovative product, and zero otherwise[5]. Second, to check the role of inputs for innovation, we define the variable input-using innovation ("*input-using innovation*") which takes value one if the firm reports that the main innovative product uses different inputs than products it was already producing, and zero if it either did not use different inputs or did not innovate at all. Of all innovating firms, 58% report the use of different inputs for their main innovation, so new inputs appear as an important feature of innovation. Finally, we go one step beyond the self-reported use of new inputs and define a new variable that captures whether one or more new inputs are essential to the product innovation

[5] It is the self-reported answer to the question: 'From fiscal year 2010 to 2012, did this establishment introduce any innovative product or service?', where "innovative" is explicitly defined as "new or significantly improved", and 'new' can be new to firm.

("*input-essential innovation*"). This variable takes value one if using new inputs is essential to the innovation and zero if no innovative products were introduced or if new inputs were not essential. To classify an innovation as input-essential, we examine the firm's description of its main product innovation and look for a reference to the use of a particular (material) input. We find that 38% of the product innovating firms with non-missing descriptions describe the use of a (new) input for their product innovation. Consider for example a firm describing its main innovative product as a toothpaste that uses new chemicals compared to the previous toothpaste it produced. This answer suggests that the use of a new input is at the core of the innovation and we define it as an "input-essential innovation". Under this definition, not all input-using innovations are input-essential innovation. The underlying assumption behind this method is that if an input is (not) mentioned in the innovation's description, it is (not) an essential feature of the innovation. While this method depends on the subjective perception of the respondent, the answers from firms are the best large-scale proxy to the importance of inputs for innovations that we can obtain in developing countries. Section A in the Appendix outlines the procedure for computing this new variable in more detail.

4.3. Measuring input varieties

Using UN Comtrade import data, we calculate for each importing country (c) the number of trading partners (x) per six-digit (HS) commodity code (product) (h) in a given year (t) as well as the total imports per product $M_{h,c,t}$. In our baseline estimates, we define a 'new' variety in 2009 as a variety that is imported in 2009 but was not imported in 2008. We show in the Appendix F.1 that using different lags (e.g. defining varieties as imported in 2009 but not in 2007) yields similar results, as well as using 2010 or 2008 instead of 2009 as the base year[6]. We denote this number of new varieties in product code h imported by country c in year t as $V_{h,c,t}$. Given the measure of new varieties at the product-level we generate a measure of *input* varieties at the industry-level. First, we aggregate from six-digit product-level to two-digit (input) industry level (k) so that we obtain $V_{k,c,t}$ and $M_{k,c,t}$. This level of aggregation is due to (low) level of aggregation of the IO matrix. Using the Input-Output (IO) table we construct the following measure of new input varieties:

$$NIV_{j,c,t} = \sum_{k} (\alpha_{j,k} \cdot V_{k,c,t}), \tag{3}$$

[6]The robustness of our results to using pre-crisis years only for international trade is in that sense reassuring.

where $\alpha_{j,k}$ is the share of input k (as a fraction of total inputs) used by industry j. Similarly, we compute a measure of total imports of the industries supplying inputs to industry j as:

$$IM_{j,c,t} = \sum_{k} (\alpha_{j,k} \cdot M_{k,c,t}). \tag{4}$$

We take the Indian IO matrix for all countries and it is therefore constant across time and space. Because the IO matrix is not available for all countries in our sample, we employ the commonly used Indian IO matrix. Moreover, taking one IO matrix for all countries ensures that the within-industry (across country) variation in imported varieties stems from trade differences only and not from differences in IO coefficients. While in theory large differences in the true (unknown) IO-coefficients may be a concern, di Giovanni and Levchenko (2010) find reassuring evidence that the IO matrices of 55 OECD and non-OECD countries are quite similar across countries.

The growth of imported inputs in (1) is equal to $ln(IM_{j,c,t}) - ln(IM_{j,c,t-1})$. We control for the growth in imported inputs so that the number of newly imported inputs - an extensive margin variety effect - can be differentiated from an intensive margin effect. The full list of variables, their description and data source can be found in Table B.1 in Appendix B.

4.4. Endogeneity

A concern in our estimation of regression equation (1) is that imported varieties may be correlated with unobservables, in particular industry-specific import demand shocks. Suppose for example that producers develop product innovations in response to a domestic demand shock and that these new or improved products require more imported varieties. Also, the estimation may suffer from reverse causality bias if innovative firms are more likely to import intermediate inputs. While there is no empirical evidence linking innovation to importing, previous research has found that productive firms are more likely to export (see for example Wakelin (1998); Bernard and Jensen (1999); Aw et al. (2000); Alvarez and Lopez (2005); Damijan and Kostevc (2015); Şeker (2012)), and thus the decision to innovation and the decision to import may be correlated as well. In both cases, the OLS estimate of the effect of imported varieties on innovation may be biased upward.

We pursue a number of strategies to identify the causal effect of industry-level import varieties on firm-level product innovation. First, we control for a number of variables that are potentially correlated with both imported varieties and innovation, including firm size (employment), sales, productivity, and the degree of competition, following for example Almeida and Fernandes (2008) and Alvarez and Robertson (2004).

Second, we exploit time variation in the trade data. While the innovation data is a cross-section of firms, we measure the number of newly imported varieties at the beginning of the innovation period. These varieties that were previously unavailable make the development of new product innovations feasible. Moreover, given that it may take some time between availability of the input and the realization of the product innovation, the relevant measure of imported variates is at the start of the innovation period. A threat to this strategy is that both innovation and imported input varieties may be correlated over time.

Therefore, our third strategy is an instrumental variables (IV) estimation that accounts for the potential endogeneity of imported varieties. To isolate the supply-driven component of imported varieties, we instrument for the number of new input varieties in industry k in country c using the number of new input varieties in industry k in a similar country s. We define a country s as most similar to country c if its ranking on the Global Competitiveness Index (GCI) is closest to country c's ranking within its geographical region (South Asia for Bangladesh; Sub-Saharan Africa for Kenya, Tanzania, Uganda and Ghana). The Global Competitiveness Report is published by the World Economic Forum every year and ranks countries based on their competitiveness which is defined as "the set of institutions, policies, and factors that determine the level of productivity of a country"(Schwab and Porter, 2008, pp.3). The GCI is a composite measure of a large set of indicators covering 12 different topics ('pillars') that include amongst others institutions, macroeconomic stability, eduction, financial markets, and innovation. Due to the similarity in economic structure, we expect the number of imported varieties at the industry level in similar countries to be correlated with the number of imported varieties in our sample countries[7]. While these paired countries may be different in many respects, their similarity in competitiveness as measured by similarity in institutions and policies that affect productivity is an important reason why we except the number of imported varieties to be similar across industries as well. The IV strategy will produce an unbiased coefficient estimate of the effect of imported varieties if the common between-industry variation of new imported varieties is driven by exogenous factors such as falling trade costs and rising comparative advantage of the exporting countries. This strategy may fail if industry product demand shocks are correlated across similar countries. A decline in demand in an industry in country c may, through trade, directly affect industry demand the same industry in a similar country which in turn affects imports in both countries. Alternatively, the industries in

[7]The similar countries are: Senegal, Ethiopia, Zambia, Cameroon and Pakistan for Kenya, Uganda, Ghana, Tanzania and Bangladesh, respectively.

these countries may be subject to the same external demand shock. In both cases, the exclusion restriction is violated and the IV estimates are again biased. Therefore, we propose an alternative instrument that is based on the costs to import at the industry-country level. Variation in import costs has been identified as an exogenous and relevant source of variation in the import of new intermediate inputs. Whereas Goldberg et al. (2010) exploit exogenously imposed changes in import tariffs, Colantone and Crinò (2014) use transportation costs which vary both over time (oil prices) and across industries (weight). We use the number of days it takes to clear inputs through customs in industry j in country i (customs delay) as an instrument for new import varieties. An efficient and speedy customs clearing process should ease trade and increase the number of newly imported intermediate inputs.

4.5. Chinese varieties

The large increase in Chinese exports in the past few decades has had a significant impact on productivity in the European Union (Bloom et al., 2016) and employment in the United States (Autor et al., 2013). Compared to 2005, the Chinese have supplied an increasing share of total import varieties and in all our sample countries, China ranks first or second as variety supplier (see Appendix D for an overview of the main import partners per country). Nevertheless, there exists little empirical evidence on the effect of Chinese exports on the performance of domestic firms in developing countries. This research aims to fill this gap.

Next to being an interesting case to study, the recent surge in China's export is likely to represent a clear 'push' factor, allowing us to isolate the effect of trade liberalization from 'pull' factors such as increased domestic demand. The integration of China in the global economy in the 2000's has been a striking phenomenon, with a wide array of consequences for many countries. Figure 1 shows the growth of Chinese exports to the world and to the five countries considered in this study, where we normalize the 2004 value to 100. We also report the growth of the number of exporting firms to the world and to our five countries. While Chinese export growth to the world has been massive, exports to the 5 countries considered in this study grew even stronger, by a factor 10 from 2004 to 2012. This growth came hand in hand with a large expansion of the number of Chinese firms exporting to the world and to the 5 countries in our analysis[8].

[8] The jump in 2006 may partly be an artifact of the Chinese Customs data, which seems to undergo a structural break between 2006 and 2007. For example, the total value of exports when adding firm-level CCTS data is smaller than the value of exports in COMTRADE before 2006 but is exactly in line from 2007 onwards. We use the 2007-2009 changes in our analysis to avoid that the results be driven by the 2006-2007 change but the analysis is robust to using 2005-2009.

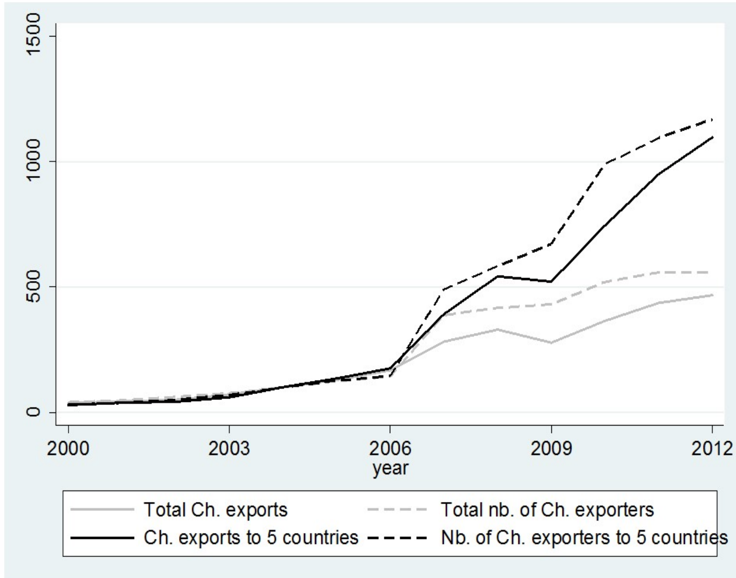

Figure 1: Expansion of Chinese trade to the world and to the 5 countries. Each series is normalized to a 100 in 2004. Source: CCTS.

Furthermore as stated in Section 3.2.2, the Chinese dataset is sufficiently detailed that we can define the number of imported varieties of a product in a country as the number of Chinese firms selling that product in the country. We thus examine the effect of the number of Chinese firm varieties (where a variety is a firm supplying a product) on innovation. Despite the plausibility that China's export growth was primarily driven by a reduction in global trade barriers (Autor et al., 2013), the regression may still be prone to the endogeneity concerns explained in Section 4.4. To estimate the causal effect, we run two IV regressions. First, we use the number of Chinese input varieties in industry k in a similar country s as instrumental variable. Second, we compute a measure of Chinese export supply capability using a method developed by Autor et al. (2013). By estimating a gravity equation of relative export which differences out import demand in the importing country, we can isolate the variation in exports due to comparative advantage and trade-cost differences. Because concerns about supply shocks in the importing country cannot be ruled out, we estimate the Chinese export supply capability vis-à-vis the USA and interact the change in this measure with the country (c) - industry (j) share of Chinese imports. The details of this method are described in described in Appendix E.

4.6. Summary statistics

Table 3 below provides some summary statistics on the innovation variables and new input varieties in 2009. About half of the firms in our sample introduced a product innovation, which is double the average for European countries of 23.7 percent (EU-28; or 26.9% in EU-15) in 2012[9]. Finding higher propensities to innovative in developing countries is not uncommon. For example Almeida and Fernandes (2008) find a difference of 20 percentage points between the percentage of innovative firms in 47 developing countries (using data from the World Bank Investment Climate Surveys) and that in European countries. A possible reason for this difference is the relative size of different industries with different propensities to innovate[10], although the most likely cause is a different interpretation of what is 'new' or 'significantly' improved. There is considerable variation in input varieties in 2009, and about one-third of the firms uses at least some inputs of foreign origin in their production process, and a quarter directly imports materials or supplies.

Table 3: Summary statistics

Variable	Mean	St.Dev.	Min	Max	N
Product innovation	0.48	0.5	0	1	1895
New input product innovation	0.28	0.45	0	1	1888
Input-essential product innovation	0.13	0.34	0	1	1537
New input varieties 2009	143.67	67.39	41.67	401.43	1893
Import growth of inputs 2009	-0.13	0.17	-1.52	0.26	1893
Import growth of output 2009	-0.1	0.51	-2.63	2.25	1862
Customs delay	16.23	14.8	1	120	1467
Share of inputs of foreign origin	0.31	0.37	0	1	1813
Direct importer	0.25	0.43	0	1	1868

Details on the variable description and data sources are in Appendix B.

5. Empirical results

5.1. Ordinary least squares

5.1.1. Effect of input variety on innovation

This section reports the results of regressing innovation between 2009-2012 on the log of the number of new input varieties on product innovation. A variety is defined as a country-product pair and a new variety is imported in the current year while not in the previous year. We take the number of new input varieties in 2009 (not imported in 2008), thus at the beginning of the innovation period, as the independent variable to reduce the potential for a reverse effect of product innovation on imported inputs. The dependent variables are innovation, new input innovation, and input-essential innovation. All regressions include four-digit industry dummies, country dummies, three

[9]Calculated using data from the European Community Innovation Survey 2012, accessed through Eurostat

[10]Tables C.1 to C.3 in Appendix C show the number of innovating and non-innovating firms per ISIC sector and country for each the three definitions of innovation.

size dummies based on employment (medium size is the omitted variable), a dummy for foreign-owned, a dummy for government-owned and age in years. We first report the results of the Ordinary Least Squares (OLS) regression in Table 4. While the outcome variable is dichotomous, we find very similar estimates of the marginal effect when estimating a probit model (reported in Appendix F.2). The regression coefficients in the odd columns suggest that, as expected, imported varieties have a positive and significant effect on product innovations, but only for those innovations that use new inputs. The effect is significantly different from zero and not unsubstantial: a 47 percent increase in the number of input varieties from the mean, corresponding to the standard deviation of 67.39 varieties, raises the probability of an innovation by about 2.7 percentage points ($\frac{47 \cdot 0.57}{100}$). The (unreported) share of variance explained by the log of new input varieties is very small: in columns 5 for example, the variable explains close to one percent of the variation. The import growth of inputs is included to control for an intensive margin effect. The number of new varieties may well be correlated with a general increase in imports, and we want to isolate the effect of variety expansion. Import growth of imports enters significantly with a negative sign in the regression with innovation and new input innovation. Of the other control variables, ownership and age are never significant, while the coefficient for foreign firms is negative and the coefficient on government-owned positive. The variable age enters negatively, but the effect is not significantly different from zero.

One interpretation of "input-essential innovations" is that one very specific input variety is necessary and having access to many varieties is irrelevant since the innovation requires only that one particular input. Then it is not the number of varieties that matters, but rather the availability of a single specif input. However, having access to that necessary input variety could very well be affected by the number of varieties imported: the more varieties imported, the larger the chance that a particular variety is imported. A more likely interpretation of the positive effect of input varieties on input-essential innovation is that having more varieties to choose from induces or inspires innovation. Consider the example in the Introduction where the firm replaced a local wood type of low quality with a higher quality imported wood. Once the foreign wood is imported and available on the local market, the firm observes this and realizes that it has the ability to improve the quality of its product (innovate) by using that wood instead of the domestic wood.

The even columns show the results of the regression when controlling for the number of new output varieties, as this may be correlated with the number of input varieties as well as innovation through an import-competition effect. In other words, as trade openness leads to more or better inputs for a company to use in its production, the company's output (product) may be subject to more competition now that more varieties of the output product are available on the domestic market. In this way, increasing openness to foreign trade can have an indirect effect on innovation in addition to the effect through imported intermediate inputs. While the former (indirect) effect is interesting, this study concerns the latter (direct) effect. We control for the number of new output varieties because it might bias the coefficient of new input varieties. While the coefficient on output variety is not significantly different from zero, including it in the regression renders the effect of input variates on new input innovation insignificant, but the effect on input-essential innovation remains significant and strong.

The results are robust to taking years 2008 or 2010 instead, and to defining a new variety in 2009 as a variety that was not imported in 2007 (instead of 2008) (see F.1). Moreover, the results in columns 3-5 in Table F.2 show that input-inessential innovations - product innovations for which new inputs was not essential - are negatively affected by new input varieties, although the effect is not significantly different from zero[11]. Nevertheless, since we do not find an effect on (total) product innovation, the input essential innovations seems to come at the cost of other types of innovation, and the non-significant effect on input-inessential innovations may be explained by the smaller sample size.

Because we aggregate the measure of new varieties from product to industry level, the number of new varieties depends in part on the number of 6-digit HS products that correspond to the IO category. Compare for example IO category 56 ('Rubber products') which has 515 products, to IO category 59 ('Coal tar products') which has 18 products. To control for this, we construct a new measure, called 'Log weighted new input varieties' which divides the number of new varieties per IO by the number of 6-digit HS products (N_j) in that IO before the input variety measure is constructed:

$$NIV^{W}_{j,c,t} = \sum_{k} \left(\alpha_{j,k} \cdot \frac{V_{k,c,t}}{N_j} \right). \tag{5}$$

Table 5 reports the results using this measure. The effect of new input varieties on input-essential innovation remains significant and strong.

5.1.2. Interactions

Table 6 reports the regression results of Eq. 2, which includes an interaction term of input variety and a measure of access to foreign inputs. Foreign input share is the share of foreign inputs in

[11] Due to missing data in the innovation's description, the sample of input-essential innovation is smaller than the other samples.

Table 4: Estimation results: Product innovation between 2009-2012 (I)

	Innovation		New input innovation		Input-essential innovation	
	(1)	(2)	(3)	(4)	(5)	(6)
Log new input varieties	0.28	0.29	0.57^{**}	0.47^{*}	0.57^{***}	0.49^{***}
	(0.19)	(0.25)	(0.23)	(0.28)	(0.14)	(0.15)
Import growth of inputs	-0.19^{*}	-0.22^{*}	-0.32^{**}	-0.45^{***}	0.041	0.030
	(0.10)	(0.11)	(0.13)	(0.13)	(0.080)	(0.092)
Log new output varieties		0.0040		0.040		0.038
		(0.052)		(0.053)		(0.030)
Import growth of output		0.030		0.055^{**}		0.0056
		(0.025)		(0.028)		(0.020)
Small	-0.017	-0.016	-0.024	-0.022	-0.038^{*}	-0.042^{**}
	(0.027)	(0.028)	(0.025)	(0.025)	(0.021)	(0.020)
Large	0.058	0.056	0.073^{*}	0.077^{*}	-0.020	-0.023
	(0.036)	(0.037)	(0.040)	(0.042)	(0.033)	(0.033)
Foreign owned	-0.028	-0.024	-0.050	-0.050	-0.011	-0.012
	(0.036)	(0.036)	(0.034)	(0.034)	(0.033)	(0.033)
Government owned	0.043	0.052	0.21	0.23	0.13	0.14
	(0.16)	(0.16)	(0.15)	(0.15)	(0.14)	(0.14)
Age	-0.001	-0.0008	-0.0005	-0.0003	-0.0004	-0.0003
	(0.00085)	(0.00086)	(0.00074)	(0.00074)	(0.00066)	(0.00067)
N	1837	1806	1830	1799	1485	1461

The table reports OLS regressions of innovation (innovation, new input innovation or input-essential innovation) between 2009-2012 on log new input varieties, import growth of inputs, log new output varieties and import growth of output in 2009. All regressions include country dummies and four-digit industry dummies. Small is a dummy that equals one if the firm has between 5 and 19 employees, large is a dummy that equals one if the firm has more than 100 employees. The omitted category is medium, a dummy that equals one if the firm has between 20 and 99 employees. The sample does not contain micro firms (less than 5 employees). Robust standard errors (clustered by 4digit-industry-country) are reported in parentheses. Significance: *10%, **5%, ***1%.

Table 5: Estimation results: Product innovation between 2009-2012 (II)

	Innovation		New input innovation		Input-essential innovation	
	(1)	(2)	(3)	(4)	(5)	(6)
Log new input varieties weighted by HS products	0.031	-0.015	0.26	0.057	0.40^{***}	0.27^{*}
	(0.18)	(0.21)	(0.23)	(0.23)	(0.14)	(0.16)
Import growth of inputs weighted by HS products	0.029	0.033	-0.0085	-0.013	0.055^{*}	0.057^{*}
	(0.042)	(0.045)	(0.047)	(0.051)	(0.031)	(0.033)
Log new output varieties weighted by HS products		0.047		0.098^{*}		0.064^{*}
		(0.051)		(0.056)		(0.035)
Import growth of output weighted by HS products		-0.0035		0.0030		-0.0052
		(0.023)		(0.026)		(0.019)
Small	-0.021	-0.019	-0.028	-0.026	-0.038^{*}	-0.042^{**}
	(0.028)	(0.028)	(0.025)	(0.025)	(0.021)	(0.020)
Large	0.057	0.059	0.071^{*}	0.083^{**}	-0.025	-0.025
	(0.036)	(0.037)	(0.041)	(0.041)	(0.033)	(0.033)
Foreign owned	-0.024	-0.020	-0.045	-0.045	-0.013	-0.014
	(0.035)	(0.036)	(0.035)	(0.035)	(0.033)	(0.033)
Government owned	0.028	0.041	0.19	0.21	0.12	0.14
	(0.16)	(0.16)	(0.15)	(0.15)	(0.13)	(0.14)
Age	-0.001	-0.001	-0.0007	-0.0005	-0.0004	-0.0003
	(0.00085)	(0.00085)	(0.00073)	(0.00073)	(0.00066)	(0.00067)
N	1837	1806	1830	1799	1485	1461

The table reports OLS regressions of innovation (innovation, new input innovation or input-essential innovation) between 2009-2012 on new input varieties in 2009, import growth of inputs, log new output varieties and import growth of output, where all variables are weighted by HS products. All regressions include country dummies and four-digit industry dummies. Small is a dummy that equals one if the firm has between 5 and 19 employees, large is a dummy that equals one if the firm has more than 100 employees. The omitted category is medium, a dummy that equals one if the firm has between 20 and 99 employees. The sample does not contain micro firms (less than 5 employees). Robust standard errors (clustered by 4digit-industry-country) are reported in parentheses. Significance: *10%, **5%, ***1%.

the firm's total inputs. The same controls as in Tables 4 and 5 are included, but not reported for sake of brevity given that their coefficient are of similar size and sign as in the previous Tables. The effect of new input varieties remains significant and the interaction term is positive for input-essential innovation, but not significantly different from zero. We thus find no evidence that firms using foreign inputs innovate more because of access to new input varieties, but rather that all firms benefit from increased foreign input variety. One potential explanation may be that firms do not know the origin of their inputs and therefore misreport the use of foreign inputs, causing a negative bias due to measurement error. It is not unlikely that firms buy their foreign inputs on the domestic market from an importer, making is difficult for the input-using firm to know the origin of the input. Moreover, the share of foreign inputs may not capture the importance of the input for the innovation if it represents only a small fraction of all inputs used. This may hold especially for firms with multiple products. Another potential explanation could be that the effect of foreign input varieties on innovation runs mainly through an effect on domestic inputs caused by increased competition from foreign input suppliers inducing domestic input producers to produce better of different intermediate inputs. While the output variety coefficient (which could drive this effect) was positive but insignificant in Table 5, the growth of output enters significantly in the fourth column, providing some evidence in favor of this channel. The data unfortunately, does not allow us to further investigate what explains the insignificant interaction effect.

The interaction term remains insignificant if the measure of foreign exposure is instead a dummy for direct exporter, or if four-digit industry-country dummies are included, in which case the input variety effect itself cannot be estimated due to collinearity, but the interaction term remains insignificant[12].

5.1.3. Channel

To get a better understanding of the channel through which new varieties may positively affect product innovation, we use data from the World Bank Enterprise Innovation Capabilities survey, which asks firms that use foreign inputs why these inputs were sourced abroad rather than domestically. Based on this information we create four dummy variables that equal one if the firm finds the following reasons important, respectively: (1) there are no domestic suppliers, (2) similar domestic inputs are more expensive, (3) similar domestic inputs are of poor quality, (4) similar domestic inputs are too unreliable. These reasons are not mutually exclusive. The variables equal zero if

[12]These results are not reported for the sake of brevity but are available upon request.

Table 6: Estimation results - Interacting new varieties and access to foreign inputs

	Innovation	New input innovation	Input-essential innovation
Log new input varieties	0.31	0.70***	0.56***
	(0.21)	(0.25)	(0.15)
Import growth of inputs	-0.19	-0.31**	0.053
	(0.12)	(0.14)	(0.088)
Foreign input share	0.18	0.33	-0.20
	(0.44)	(0.38)	(0.32)
(Log new input varieties * Foreign input share)	-0.042	-0.060	0.037
	(0.090)	(0.078)	(0.063)
(Import growth of inputs * Foreign input share)	-0.027	-0.10	-0.079
	(0.25)	(0.21)	(0.15)
N	1770	1763	1427

The table reports OLS regressions of innovation (innovation, new input innovation or input-essential innovation) on log new input varieties, and log new input varieties interacted with foreign input share. All regressions include country dummies, four-digit industry dummies, three size dummies, dummies for government and foreign ownership and age. Robust standard errors (clustered by 4digit-industry-country) are reported in parentheses. Significance: *10%, **5%, ***1%.

the reason was deemed moderately important or not important. Summary statistics on these four dummy variables are reported in Table 7 below. Almost half of the firms indicate availability as important reason and the other three reasons are deemed important by one third of the firms. Note that the capability survey is administered to a subset of the WB Innovation Survey sample (which itself is a subset of the World Bank Enterprise Survey), and that this question is only answered by firms that use raw materials of foreign origin (71% of the sample, 821 firms). Moreover, the reasons for importing are not mutually exclusive: firms can report more than one reason[13].

Table 7: Reasons for importing inputs (not mutually exclusive)

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Domestic input not available	0.47	0.5	0	1	820
Domestic input more expensive	0.35	0.48	0	1	821
Domestic input of poor quality	0.33	0.47	0	1	820
Domestic input unreliable	0.3	0.46	0	1	820

Table 8 reports the results of a regression with innovation (yes/no) as dependent variable and the four reasons for importing on the right-hand side. We use the same controls and fixed effects as in the previous regressions. We find that for new input innovation and input-essential innovation, the quality reason is significant. These findings are in line with the observed increase in the variety

[13]Even the category ‘not available’ is not mutually exclusive because a firm can import more than one input.

extensive margin in Table 2 in Section 3.2, where most of the increase in new varieties was found to stem from importing more varieties of already existing products.

Table 8: Estimation results - Reasons for using foreign inputs

	(1) Innovation	(2) New input innovation	(3) Input-essential innovation
Poor quality domestically	0.028	0.069^{*}	0.090^{**}
	(0.040)	(0.041)	(0.035)
Not available domestically	-0.050	0.0093	-0.021
	(0.033)	(0.034)	(0.027)
More expensive domestically	-0.025	-0.037	-0.035
	(0.040)	(0.036)	(0.026)
Unreliable domestically	0.0021	-0.012	-0.013
	(0.036)	(0.036)	(0.030)
N	788	786	622

The table reports OLS regressions of innovation (innovation, new input innovation or input-essential innovation) between 2009-2012 on reason to use foreign rather than domestic inputs. All regressions include country dummies, four-digit industry dummies, three size dummies, dummies for government and foreign ownership and age. Robust standard errors (clustered by 4digit-industry-country) are reported in parentheses. Significance: *10%, **5%, ***1%.

5.1.4. Additional controls

Next, we control for a number of variables that are potentially correlated with both imported varieties and innovation, including firm size (employment), sales, productivity, and the degree of competition. The level of competition is captured by three dummies (weak, medium and strong, for 0-5, 6-20 or more than 20 competitors, respectively) and the missing category is medium. Labor productivity is the log of real sales over employment in 2009, and mean labor productivity is industry-country mean labor productivity in 2009. The coefficient for Log new input varieties remains significant and stable around 0.5-0.6.

Table 9: Estimation results - Additional controls

	(1) New input innovation	(2) Input-essential innovation	(3) New input innovation	(4) Input-essential innovation	(5) New input innovation	(6) Input-essential innovation
Log new input varieties	0.68^{**}	0.64^{***}	0.54^{*}	0.66^{***}	0.52^{*}	0.61^{***}
	(0.28)	(0.18)	(0.31)	(0.18)	(0.31)	(0.18)
Import growth of inputs	-0.42^{**}	-0.041	-0.30	-0.025	-0.30	-0.046
	(0.18)	(0.11)	(0.20)	(0.11)	(0.20)	(0.10)
Weak competition	-0.016	-0.00066	0.042	0.014	0.040	0.010
	(0.049)	(0.040)	(0.058)	(0.043)	(0.058)	(0.044)
Strong competition	-0.015	0.021	0.017	0.055	0.016	0.051
	(0.040)	(0.032)	(0.047)	(0.034)	(0.047)	(0.034)
Labor productivity			-0.0063	0.0067	-0.0036	0.012
			(0.0093)	(0.0081)	(0.011)	(0.0091)
Mean labor productivity					-0.013	-0.029^{*}
					(0.022)	(0.015)
N	1372	1101	1082	843	1082	843

The table reports OLS regressions of innovation (innovation, new input innovation or input-essential innovation) between 2009-2010 on log new input varieties in 2009 and additional controls competition and labor productivity in 2009. All regressions include country dummies, four-digit industry dummies, three size dummies, dummies for government and foreign ownership and age. Robust standard errors (clustered by 4digit-industry-country) are reported in parentheses. Significance: *10%, **5%, ***1%.

5.2. Instrumental variables

5.2.1. Import varieties in a similar country's industry as instrument

While using a lagged measure of input variates and controlling for a number of observed firm and industry characteristics may alleviate endogeneity concerns, the OLS coefficient estimates for imported input varieties may be still be biased if there is unobserved heterogeneity. This section reports the results of the IV estimation using the number of new input varieties in the same industry of a similar country as instrument. The results are reported in columns 1-3 in Table 10 on p. 26. The instruments is sufficiently strong as indicated by a high Kleibergen-Paap rk Wald F statistic (F-stat) which is larger than the commonly used rule of thumb value of 10, and the second-stage coefficient estimates are in line with the OLS results in Table 4.

5.2.2. Customs delay as instrument

While the instrument based on varieties in the same industry in a similar country was found to be a sufficiently strong instrument, the exclusion restriction may fail if these similar industries are prone to the same shocks. Therefore, we propose an alternative instrument that is based on the costs to import at the industry-country level. Variation in import costs has been identified as an exogenous and relevant source of variation in the import of new intermediate inputs. For example, Goldberg et al. (2010) use import tariffs and Colantone and Crinò (2014) use transportation costs based on oil prices and weight of the inputs. We compute the number of days it takes to clear inputs through customs as an instrument for the number of newly imported varieties. An efficient and speedy customs clearing process should ease trade and increase imports of new intermediate inputs. Hummels and Schaur (2013) estimate the effect of a day in transit to be comparable to an ad-valorem tariff of 2.1 percent. Both risk management systems as well as the physical time to inspect products differ along products. Whereas some products are relatively easy to inspect by having a quick look in a box or container, others may require more extensive laboratory testing (Fernandes et al., 2015). Differences in institutions drive both variation between countries (within industries), as well as within countries between industries as not only customs, but many other government agencies including health, standards and environment are involved in trade regulation. In some countries, there can be up to 30 government agencies involved in the cross-border movement of goods (Choi, 2001). The total customs clearance process, meaning the time between the good's entry into the country and when the good can be claimed by the firm, thus depends on the efficiency at each of the product's relevant agency. We use the data from the WB enterprise survey to calculate an industry-country measure of customs clearance days. Specifically, question D.3 in the WB ES reads “In the last fiscal year, when this establishment imported inputs or supplies, how many days did it take on average from the time these goods arrived to their point of entry (e.g. port, airport) until the time these goods could be claimed from customs?”. We average this measure to the industry-country level and use the log of the number of customs delay (log customs delay) as an instrument for log new input varieties. There is considerable variation in days in customs, ranging from 2 to 42.2 days (excluding bottom and top 5%), with a mean of 16.2 days and a standard deviation of 14.8 days. An analysis of the variance indicates that about two-thirds of the variation comes from differences within countries (across industries), and the remainder stems from between country differences (within industries). A potential concern is that industry characteristics that are important for innovation also affect the efficiency at the customs and other relevant government agencies. Speeding up customs time may be part of government policy to stimulate or maintain output in specific sectors, which could be in the form of protecting productive and innovative sectors or, alternatively, helping less productive industries. Reversely, productive and powerful sectors may effectively lobby for efficient import processes. We control for this by including an industry measure of labor productivity in 2009. The results are in columns 4-6 in Table 10. As expected, the number of custom days negatively affects the number of new varieties imported. The instrument’s F-statistic is close to the rule of thumb of 10. The effect of newly imported inputs on new-input innovation and input-essential innovation is larger than estimated before and remain significant. We perform two additional robustness exercises of which the results are in Appendix F.4. First, instead of taking a four-digit industry-country measure of customs delay, we take the industries at the two-digit levels. The effect of newly imported varieties on new input innovation is similar in size and remains significant, while the effect on input-essential innovation is non-significant. The low F-stat (close to 3) in the first-stage, driven by the less precise measure of customs delay, however, indicates that the second stage results can be biased and may suffer from large standard errors. Second, to reduce endogeneity in the self-reported customs delay measure, we restrict the sample to non-direct importers only. While these firms do not import intermediate goods directly from abroad, they may benefit from a larger pool of foreign inputs that are imported by other firms and resold on the domestic market. Also here, the effect of newly imported varieties on new input innovation remains significant.

Table 10: Estimation results - Instrumental variables estimation (I)

	Inputs in similar country			Customs delay		
	(1) Innovation	(2) New input innovation	(3) Input-essential innovation	(4) Innovation	(5) New input innovation	(6) Input-essential innovation
Panel A: Second stage						
Log new input varieties	0.60	0.39	0.49**	0.54	1.56**	0.81*
	(0.41)	(0.41)	(0.21)	(0.77)	(0.66)	(0.45)
Panel B: First stage Input Varieties						
Log new input varieties in similar Country	0.47***	0.46***	0.46***			
	(0.064)	(0.063)	(0.065)			
Log customs delay				-0.031***	-0.031***	-0.028***
				(0.0097)	(0.0096)	(0.0098)
Small	-0.0045	-0.0046	-0.0050	-0.0094*	-0.0094*	-0.0096*
	(0.0048)	(0.0049)	(0.0055)	(0.0048)	(0.0050)	(0.0053)
Large	-0.0057	-0.0058	-0.0063	-0.0019	-0.0020	-0.0040
	(0.0053)	(0.0053)	(0.0055)	(0.0050)	(0.0051)	(0.0048)
Foreign owned	-0.0051	-0.0042	-0.0078	-0.0020	-0.0012	-0.0046
	(0.0045)	(0.0047)	(0.0051)	(0.0055)	(0.0057)	(0.0059)
Government owned	-0.037	-0.039	-0.050	-0.023	-0.024	-0.038
	(0.024)	(0.025)	(0.033)	(0.018)	(0.019)	(0.027)
Age	-0.00013	-0.00012	-0.00014	-0.0002*	-0.0002*	-0.0002*
	(0.00011)	(0.00010)	(0.00010)	(0.00011)	(0.00010)	(0.00010)
N	1837	1830	1485	1418	1412	1136
F-stat	53.7	54.4	49.6	10.2	10.2	8.42

The table reports IV regressions of innovation (innovation, new input innovation or input-essential innovation) between 2009-2012 on log new input varieties in 2009. In columns 1-3, the instrument is log new input varieties in the same industry in a similar country (see Section 4.4 for the similar countries) and in columns 4-6, the instrument is log customs delay, which is the number of days an input is kept in customs. All regressions include country dummies, four-digit industry dummies and the industry's mean labor productivity in 2009. Small is a dummy that equals one if the firm has between 5 and 19 employees, large is a dummy that equals one if the firm has more than 100 employees. The omitted category is medium, a dummy that equals one if the firm has between 20 and 99 employees. The sample does not contain micro firms (less than 5 employees). Robust standard errors (clustered by 4digit-industry-country) are reported in parentheses. Significance: *10%, **5%, ***1%.

5.2.3. Including both instruments

Because we have two instruments, we can also use them together in the instrumental variable estimation. Given that both instruments add useful and independent variation, including them both is more efficient than running two separate regressions. The results are reported in Table 11. The first-stage results indicate that indeed the instruments are jointly relevant, and their size and sign is comparable to those in Table 10. The F-stat is lower than when including only log inputs in similar country as instrument, but still sufficiently high. The second-stage effect of newly imported varieties on input-essential innovation is significant and similar in size to the coefficient reported in Column 3 of Table 10. Because we have more instruments than endogenous regressors, we can also test of over identifying restrictions. The Hansen J p-value is larger than 0.1 in all specifications, and therefore we cannot reject the null hypothesis that the over-identifying restrictions are valid.

Table 11: Estimation results - Instrumental variables estimation (II)

	(1) Innovation	(2) New input innovation	(3) Input-essential innovation
Panel A: Second stage			
Log new input varieties	0.51	0.63	0.58***
	(0.50)	(0.53)	(0.21)
Small	-0.020	0.00054	-0.022
	(0.033)	(0.031)	(0.025)
Large	0.045	0.063	-0.021
	(0.041)	(0.047)	(0.039)
Foreign owned	-0.027	-0.048	-0.014
	(0.040)	(0.041)	(0.038)
Government owned	0.12	0.27*	0.11
	(0.18)	(0.16)	(0.17)
Age	-0.0011	-0.00019	-0.00034
	(0.00099)	(0.00083)	(0.00076)
Panel B: First stage Input Varieties			
Log new input varieties in similar country	0.47***	0.47***	0.49***
	(0.069)	(0.068)	(0.067)
Log customs delay	-0.018**	-0.018**	-0.016*
	(0.0092)	(0.0091)	(0.0087)
N	1418	1412	1136
F-stat	29.2	29.6	32.1
Hansen J p-value	0.95	0.16	0.59

The table reports IV regressions of innovation (innovation, new input innovation or input-essential innovation) between 2009-2012 on log new input varieties in 2009. The instruments are log new input varieties in the same industry in a similar country (see Section 4.4 for the similar countries) and log customs delay, which is the number of days an input is kept in customs. All regressions include country dummies, four-digit industry dummies and the industry's mean labor productivity in 2009. Small is a dummy that equals one if the firm has between 5 and 19 employees, large is a dummy that equals one if the firm has more than 100 employees. The omitted category is medium, a dummy that equals one if the firm has between 20 and 99 employees. The sample does not contain micro firms (less than 5 employees). Robust standard errors (clustered by 4digit-industry-country) are reported in parentheses. Significance: *10%, **5%, ***1%.

6. A variety as a firm-product: China

We now turn to studying how the emergence of China impacted firm-level innovation in our five developing countries. As explained in Section 4.5, next to being an interesting case to study, the Chinese data provide a number of benefits over the previous analyses using world-level trade data supplied by UN Comtrade. First, the large increase in Chinese exports is likely to represent a considerable push factor, thus reducing the concern for reverse endogeneity through pull factors. Second, unlike the UN Comtrade dataset, the Chinese data is recorded at the firm-product level.

We conduct a similar exercise as in Section 4.3, where we now define the number of Chinese varieties $N_{k,c,t}^{CH}$ as the number of Chinese *firms* that export product code k (4-digit) to importing country c in year t[14] and where $M_{k,c,t}^{CH}$ is the value of imports of input k by country c in year t from China. We then construct the number of Chinese input varieties in an industry and the value of imported inputs as:

$$N_{j,c,t}^{inp,CH} = \sum_k \left(\alpha_{j,k} \cdot N_{k,c,t}^{CH}\right), \tag{6}$$

$$M_{j,c,t}^{inp,CH} = \sum_k \left(\alpha_{j,k} \cdot M_{k,c,t}^{CH}\right). \tag{7}$$

Table 12 shows some summary statistics on the Chinese firm-level variety measure in 2005 and 2009. Such a growth can *a priori* be due to push factors (a Chinese supply shock) or pull factors (a demand shock in our 5 countries). As a first impression on the importance of each factor, we show the evolution of the number of French firms (using data from the French customs) exporting to our 5 countries between 2005 and 2009. Two observations stand out. First, the number of Chinese varieties is much larger than French varieties. Given the share of Chinese imports and the small share of French imports in our sample countries, this is not surprising. Second, the number of Chinese input varieties has increased significantly between 2005 and 2009, whereas the number of French firms has remained almost the same, suggesting that the push factor is the main driver of the number of Chinese varieties.

We test the link between imports of Chinese inputs and firm-level innovation using different variants

[14] Note that we here use the log number of varieties and not the number of new varieties as in the previous analysis. The reason is that we do not yet have data on the number of new varieties but only on the total number of varieties sold to a country in a year.

Table 12: Chinese and French input varieties: 2005-2009

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Chinese input varieties 2005	60.55	52.46	0.6	190.4	1893
Chinese input varieties 2009	250.52	178.18	3.23	683.85	1893
French input varieties 2009	1.33	1.54	0.01	11.52	1893
French input varieties 2005	1.22	1.86	0.01	15.06	1893

of the following equation:

$$\begin{aligned} INN_{ijc} = & \quad \beta_0 + \beta_1 \ln\left(N^{inp,CH}_{j,c,2009}\right) + \beta_2 \ln\left(M^{inp,CH}_{j,c,2009}\right) + \beta_3 \ln\left(NIV_{jc}\right) \\ + & \quad \beta_4 IMG_{jc} + \beta_5 \ln\left(N^{CH}_{j,c,2009}\right) + \beta_6 \ln\left(M^{CH}_{j,c,2009}\right) + \boldsymbol{\gamma X_{ijc}} + \varepsilon_{ijc}, \end{aligned} \tag{8}$$

where we keep the same set of controls X_{ijc} as in Table 4 and introduce the main regressors in turn. The results are reported in Table 13. In columns 1, 4 and 7 we only use the two measures of Chinese imported inputs (the number of varieties $N^{inp,CH}_{j,c,2009}$ and the value of imported inputs $M^{inp,CH}_{j,c,2009}$) as our main regressors. While these are jointly significant for all types of innovations, the number of imported inputs only appears significantly positive when using the input-essential innovation as our measure. We then add in columns 2, 5 and 8 the controls for input imports that we used in Table 4 and show that, again in the case of input-essential innovations, both the number of imported inputs from China and the new imported varieties defined as country-product pairs appear significant. Finally, we show in columns 3, 6 and 9 that these patterns are robust to controlling for a potential import competition effect measured by the number of varieties and the value of imports in the firms' output industry. The positive link between Chinese exports and product-innovation in developing countries balances empirical studies that find a negative impacts of China's exports on the exports of other Asian and African countries (Giovannetti and Sanfilippo, 2009; Eichengreen et al., 2004)[15]. It may seem counter-intuitive that intermediate inputs from China, a country that has a low position on the quality ladder (as suggested by Schott (2008) and Kneller and Yu (2008)), can have a substantial contribution to innovation. However, our sample consists of developing countries whose domestic intermediate goods are likely to be of the same or even lower quality. Moreover, while inputs from high income countries may carry the best available technology, they may be less appropriate for developing countries due to the gap in technology and the resulting low absorptive capacity. For developing countries, Chinese imported inputs may be of better quality without being too far away (or too expensive) in terms of technology. Moreover,

[15] Athukorala (2009) warns, however, that although some crowding-out effects are present, these effects are vastly overstated in the current policy debate.

our definition of innovation includes incremental changes that are new to the firm only, which is less likely to require high technology.

Table 13: Estimation results - Log Chinese input (firm) varieties and product innovation

	Innovation			New input innovation			Input-essential innovation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Ch. input varieties	0.073	0.056	0.076	0.20	0.13	0.25^{*}	0.26^{***}	0.18^{**}	0.24^{***}
	(0.13)	(0.14)	(0.16)	(0.13)	(0.14)	(0.15)	(0.091)	(0.085)	(0.087)
Log Ch. imports of inputs	0.056	0.035	0.019	0.036	-0.021	-0.034	-0.089^{*}	-0.090	-0.093
	(0.086)	(0.100)	(0.11)	(0.082)	(0.095)	(0.095)	(0.053)	(0.057)	(0.058)
Log new input varieties		0.11	0.26		0.42	0.32		0.51^{***}	0.46^{**}
		(0.21)	(0.29)		(0.26)	(0.34)		(0.15)	(0.18)
Import growth of inputs		-0.10	-0.16		-0.26	-0.35^{**}		0.041	0.042
		(0.14)	(0.14)		(0.17)	(0.17)		(0.087)	(0.085)
Log Ch. output varieties			0.022			-0.012			-0.051^{**}
			(0.038)			(0.040)			(0.020)
Log Ch. imports of output			-0.0014			0.011			-0.0012
			(0.015)			(0.015)			(0.0085)
Log new output varieties			-0.042			-0.00013			0.086^{*}
			(0.091)			(0.079)			(0.047)
Import growth of output			0.083^{**}			0.11^{***}			-0.0062
			(0.034)			(0.032)			(0.024)
Small	-0.017	-0.016	-0.018	-0.024	-0.023	-0.030	-0.039^{*}	-0.038^{*}	-0.051^{**}
	(0.027)	(0.027)	(0.028)	(0.025)	(0.025)	(0.025)	(0.021)	(0.021)	(0.020)
Large	0.056	0.057	0.046	0.070^{*}	0.072^{*}	0.066	-0.023	-0.020	-0.030
	(0.036)	(0.036)	(0.037)	(0.040)	(0.040)	(0.041)	(0.033)	(0.032)	(0.033)
Foreign owned	-0.023	-0.025	-0.028	-0.043	-0.049	-0.053	-0.019	-0.014	-0.023
	(0.036)	(0.036)	(0.037)	(0.035)	(0.034)	(0.035)	(0.032)	(0.032)	(0.032)
Government owned	0.041	0.044	0.011	0.20	0.22	0.21	0.11	0.12	0.14
	(0.16)	(0.16)	(0.17)	(0.15)	(0.15)	(0.16)	(0.13)	(0.14)	(0.14)

Continued on next page

Table 13 – *Continued from previous page*

	Innovation			New input innovation			Input-essential innovation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age	-0.0011	-0.0011	-0.00061	-0.00063	-0.00051	-0.00035	-0.00054	-0.00048	-0.00031
	(0.00085)	(0.00085)	(0.00087)	(0.00074)	(0.00074)	(0.00077)	(0.00065)	(0.00065)	(0.00069)
N	1837	1837	1738	1830	1830	1731	1485	1485	1403

The table reports OLS regressions of innovation (innovation, new input innovation or input-essential innovation) between 2009-2012 on log Chinese (firm) varieties in 2009. All regressions include country dummies, four-digit industry dummies, three size dummies, dummies for government and foreign ownership and age. Robust standard errors (clustered by 4digit-industry-country) are reported in parentheses. Significance: *10%, **5%, ***1%.

6.1. Import varieties in a similar country as instrument

The OLS estimation presented in Table 13 is subject to the same endogeneity issues as described in Section 4.4. We run two IV regressions. First, we perform a similar exercise as Section 5.2.1, and instrument the number of Chinese varieties in 2009 as well as the value of imports from China in 2009 by the number of Chinese varieties and the value of Chinese imports in a similar country in 2007. The results, shown in columns 1 to 3 of Table 14 broadly confirm the results of the OLS regressions and show that the number of Chinese varieties plays a particular role for input-essential innovations. While instrumenting by the explanatory variables for a similar country in 2009 (thus prior to the innovation period) alleviates these immediate endogeneity issues, endogeneity concerns may remain in the presence of both cross-country and serial correlation of the variables.

Table 14: Estimation Results - Chinese varieties: IV estimation

	Inputs in similar country						Export-supply capability		
	(1) Innovation		(2) New input innovation		(3) Input-essential innovation		(4) Innovation	(5) New input innovation	(6) Input-essential innovation
Panel A: Second stage									
Log Ch. Input	-0.25		0.26		0.66^{***}		0.056	0.21	0.064
varieties (A)	(0.34)		(0.35)		(0.24)		(0.13)	(0.16)	(0.11)
Log Ch. imports	0.22		0.072		-0.27^{*}				
of inputs (value) (B)	(0.19)		(0.20)		(0.14)				
Panel B: First stage Input Varieties									
	(A)	(B)	(A)	(B)	(A)	(B)			
Log Ch. input var.	0.097	-0.53^{**}	0.098	-0.53^{*}	0.12	-0.50^{*}			
similar country 2007	(0.17)	(0.27)	(0.17)	(0.27)	(0.16)	(0.27)			
Log Ch. imports	0.19^{***}	0.52^{***}	0.19^{***}	0.52^{***}	0.18^{***}	0.49^{***}			
of inputs similar	(0.060)	(0.085)	(0.060)	(0.085)	(0.060)	(0.084)			
Δ Export cap.							0.28^{***}	0.28^{***}	0.29^{***}
x initial Ch. exposure							(0.044)	(0.044)	(0.045)
N	1837		1830		1485		1645	1638	1322
F-stat	9.46		9.33		10.3		39.4	39.1	43.3

The table reports IV regressions of innovation (innovation, new input innovation or input-essential innovation) between 2009-2012 on log Chinese (firm) varieties in 2009. In columns 1-3, the instrument is log Chinese varieties in the same industry in a similar country (see Section 4.4 for the similar countries) and in columns 4-6, the instrument is change in export capability interacted with initial exposure to Chinese imports. All regressions include country dummies, four-digit industry dummies, three size dummies, dummies for government and foreign ownership and age. Robust standard errors (clustered by 4digit-industry-country) are reported in parentheses. Significance: *10%, **5%, ***1%.

6.2. *Chinese export capabilities as instrument*

As an alternative instrument, we use the exogenous variation in China's export supply capability at the industry level, interacted with a country-industry measure of initial exposure to China. We estimate China's export-supply capability (EC) using the Autor et al. (2013)'s fixed-effects gravity estimation of relative exports using UN Comtrade data (for see details in Appendix E). This procedure identifies the industry-specific changes in Chinese supply capability over time, as well as the change in the average costs of exporting Chinese goods to the world. We interact the change in this industry-specific measure between 2007 and 2009 (results are similar using other time differences) with a country-industry specific exposure to Chinese imports, defined as the average share of imports from China in a country-industry pair between 2002 and 2005. While we instrument only for the number of Chinese varieties in 2009, this strategy should be seen as capturing the total effect of Chinese trade - both through the number of varieties and the value (results are similar using value instead of varieties as the instrumented variable). In fact, the instrument we use can explain both margins of Chinese imports and cannot be seen as a way to disentangle the two. The estimates, reported in columns 4-6 in Table 14 show that the instrument is strong but that there is no clear evidence in favor of a causal impact of Chinese imports of inputs on any type of product innovations that we consider. Unreported results show that adding the other variables used in Table 13 as uninstrumented controls does not affect any of the IV results reported in Table 14.

7. Conclusion

Innovation is considered central to growth in developing countries. Even when innovations are incremental and only new to the firm, they can bring important changes that improve welfare. Understanding the determinants of innovation is therefore of great importance to policy makers. This research contributes to a recent and growing literature on the effect of intermediate inputs on innovation, productivity and growth. Combining quantitative trade data with survey data from five developing countries - including a novel detailed survey on innovation - we showed that the number of new intermediate input varieties has a significant positive and sizable impact on product innovations that use new inputs and in particular innovations for which a new input is an essential feature. Making use of quantitative data on the product innovation, this finding is supported by establishing a link between imported varieties and innovations for which new inputs are an essential feature. The results are robust to controlling for the number of new varieties at the output level, which may induce an import competition effect, and are robust to instrumental variables estimations. We provide suggestive evidence that the intermediate input effect comes from access to better quality imports, but are unable to confirm that foreign-input using firms benefit more from increased varieties. Our research thus indicates that openness to trade is an important contributor to input-essential innovations in developing countries through its effect on the availability of new input varieties. Policies to increase openness may therefore have a positive effect on the economy through increased innovation, although there seems to be a substitution effect from non-input using innovations to innovations that use new inputs. In fact, the net effect on total innovation is zero. Despite the importance of Chinese imports, we find no robust evidence in support of an innovation effect from Chinese firm varieties. Further research on the origin effect of imported intermediate inputs is warranted to base thorough conclusions on this finding. Innovation has gained a more important role in firm-level surveys, but there is need for more detailed questions on the role of imports in innovation to better understand this effect.

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Appendix A Defining input-essential innovation

The Innovation Follow-up Survey (IM) of the World Bank Enterprise Survey (ES) contains two open questions that are used for the construction of the variable input-essential innovation. Specifically, HB5x describes the main innovative product and HB7x describes how the main innovative product is different than the most similar product already produced by the firm. Using this descriptive information, we aim to capture product innovations for which new inputs played an essential role, as opposed to product innovations that did not require new inputs.

The variable input-essential innovation is coded either 1 (yes), 0 (no) or . (missing) based on specific words or combinations of words that occur in the innovation's descriptions. We follow definitions from the Oslo Manual which contains guidelines for collecting and interpreting technological innovation data (OECD and Eurostat, 2005) - including the annex based on the Bogotá Manual (Jaramillo et al., 2001) aimed at less-developed and non-OECD countries. We start with 908 product innovation which may or may not be input-essential innovations. First, we try to reduce some of the measurement error stemming from the fact that respondents may not fully understand the survey question on product innovation. A commonly made mistake is to confuse product with process innovation or marketing innovation. For this purpose, we set the variable for product innovation equal to missing (and thus new input innovation to missing) if HB5x or HB7x contains one of the following words: machine, manual, technology, logo, design, package, packaging. This is the case for 128 observations. Second, for the remaining 780 product innovations, we classify them as input-essential innovations if the descriptions of the innovative product contains one of the following words: using, use, used, uses, ingredient, ingredients, input, inputs, recipe, made from, made of, material, materials. We rule out the word combinations industrial use, purpose use, used to, used as, used on, used not. Third, we classify the innovation as input-essential if the respondent self-reports having used a new input for the innovation (question Hb9b in the WB ES)[16] *and* the descriptions mentions a specific input. We require both to rule out the use of new inputs that were not so essential, based on the premises that if they were essential, they would be mentioned in the description. An example of such a description for which the innovation is classified as input-essential innovation is "earlier [we] made toothpaste with normal chemicals and now [we] make toothpaste with improved chemicals". After a having a look at the descriptions, the following

[16] Without requiring a positive answer to HB9b, we might define innovations as input-driven, while the input is not new to the firm.

inputs were found: aluminum, polythene, carbonate, carbonate, chemicals, cloth , concrete, cotton, flavor, metal, paper, plastic, polyester, rubber, silk, soya, timber, tin, wood, wooden, yarn, leather. Finally, the variable input-essential innovation is set to missing if there is no answer to HB5x and HB75x

Table A.1 below reports the cross-tabulation between input-essential innovation and new input innovation. Note that the sample of 780 is innovators only, excluding innovations that were classified as process, organizational or marketing innovation.

Table A.1: Cross-tabulation of input essential and new input innovation

	New input innovation (HB9b)			
Input essential innovation	No	Yes	Missing	Total
No	**220**	24	0	344
	63.95	36.05	0.00	100.00
Yes	33	**173**	0	206
	16.02	83.98	0.00	100.00
Missing	69	156	5	230
	30.00	67.83	2.17	100.00
Total	322	453	5	780
	41.28	58.08	0.64	100.00

First, we note that the number of missing descriptions is fairly large, which is a downside of using the quantitative data. Second, for the non-missing data, we find that when an innovation is classified as input-essential, 173 firms (84%) have self-reported use of new inputs. The other 33 firms which report not using new inputs, but in 31 cases the description in HB7x clearly mentions using a different input. Our procedure thus reduces measurement error in the variable product innovation (HB9b). The other two may be misclassification as one description mentions what the product is used for, and one mentions using the same input as for its other (old) products. Third, for the non-missing data, we find that when an innovation is classified as not input-essential, 124 firms (64%) have self-reported use of new inputs. This may be driven by exactly what we are aiming to capture, namely that a in subset of the new input using innovations, these new inputs were not essential to the innovation. On the other hand, it may also be that a new input is used, but its use is too obvious and therefore not mentioned in the innovation's description. For example, if a firm used to make cement and its new product is soap, it's probably too obvious for the respondent to mention that this new product required new or different inputs. While the former will decrease measurement error, the latter may actually increase the error as we wrongly classify the innovation as not input-related, while it actually is. In the regression analysis, this effect will bias the estimated coefficient downwards, which means we have to interpret the coefficient estimate as a lower-bound estimate for the true effect.

Appendix B List of variables, description and data sources

Table B.1: List of variables, description and data sources

Variable	Description	Source
Innovation outcomes		IM
Innovation	1 if the firm introduced an innovative product, 0 otherwise	IM
New input innovation	1 if the firm introduced an innovative product using new inputs, 0 otherwise	IM
Input-essential innovation	1 if the firm introduced an innovative product for which a new input was essential, 0 otherwise	IM
Input non-essential innovation	1 if the firm introduced an innovative product for which a new input was not essential, 0 otherwise	IM
Number of innovations	number of innovative product	IM
Varieties		
Total input varieties	The number of product varieties in each input-supplying industry, weighted by the input share	Comtrade
New input varieties	The number of new product varieties in each input-supplying industry, weighted by the input share	Comtrade
New output varieties	The number of new product varieties in the firm's output product industry	Comtrade
Trade		
Growth of inputs	Total import growth in each input-supplying industry, weighted by the input share	Comtrade
Growth of output	Total import growth in the firm's output product industry	Comtrade
Chinese firm varieties		
Chinese input varieties	The number of firm varieties in each input-supplying industry, weighted by the input share	CCTS
Controls and instrument		
Size dummies	three dummies for size (5-19, 20-99 or more than 100 employees)	ES
Foreign Owned	1 if the firm is (partly) foreign-owned, 0 otherwise	ES
Government Owned	1 if the firm is (partly) state-owned, 0 otherwise	ES
Age	Years since establishment started operations	ES
Competition	Three dummies (low, medium and strong) for competition (0-5, 6-20 or more than 20 competitors, respectively)	ES
Labor productivity	Real sales divided by the number of full-time employees	ES
Custom delay	Number of days from the time inputs arrive at their point of entry (e.g. port, airport) until the time these goods can be claimed from customs	ES
Reasons for importing		
Poor quality	1 if firm imported because domestic input is of poor quality	IC
Not available	1 if firm imported because domestic input is not available	IC
More expensive	1 if firm imported because domestic input is more expensive	IC
Unreliable	1 if firm imported because domestic input is unreliable	IC

IM= Innovation Module, ES= Enterprise Survey, IC= Innovation Capabilities Module), CCTS = Chinese Customs Trade Statistics Database. An innovative product is a "new or significantly improved product (...), where "new" means new to the establishment and not necessarily new to the market". Input share are taken from the Indian 1993 Input-Output matrix.

Appendix C Sample details

Table C.1: Innovation by country and two-digit sector

	Country and Did the firm introduce a product innovation?									
	Ghana		Bangladesh		Tanzania		Uganda		Kenya	
Industry	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Food	34	10	49	75	38	8	27	33	78	43
Textiles	2	2	35	91	19	3	16	17	12	15
Garments	14	5	33	96	36	7	4	6		
Leather	2	2	59	40			1		4	2
Wood	13	1	8	7	14	1	3	4	4	1
Paper	1	2	11	15			1			2
Publishing, printing, and Recorded media	38	10	36	14	12		2	4	4	4
Refined petroleum product	2	1							2	1
Chemicals	6	11	20	69	6	1	1	2	10	18
Plastics & rubber	12	5	11	19	6	2	1	2	2	6
Non metallic mineral products	13	3	7	5	7	3	1	6	4	2
Basic metals	5	3	10	14	4		1	2	1	4
Fabricated metal products	45	6	7	18	20	2	15	16	6	4
Machinery and equipment			9	8	2		2	3	12	8
Electronics (31 & 32)	3		2	5	5	2	1	3	3	4
Precision instruments										1
Transport machines (34&35)		2	5	19	2		1	1	6	10
Furniture	16	11	14	41	51	21	13	18	5	3
Recycling		2						1		

Table C.2: New input innovation by country and two-digit sector

	Country and Did the firm introduce a product innovation that uses new inputs?									
	Ghana		Bangladesh		Tanzania		Uganda		Kenya	
Industry	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Food	38	6	78	46	41	5	44	16	95	26
Textiles	3	1	62	64	21	1	27	4	15	11
Garments	15	4	73	56	40	3	7	3		
Leather	3		77	22			1		4	2
Wood	13	1	11	4	14	1	5	2	4	1
Paper	1	2	19	6			1			2
Publishing, printing, and Recorded media	42	4	41	9	12		4	2	7	1
Refined petroleum product	2	1							2	1
Chemicals	10	7	51	38	6	1	1	2	17	11
Plastics & rubber	13	4	17	13	6	2	1	2	4	4
Non metallic mineral products	13	3	9	3	7	3	7		5	1
Basic metals	6	2	19	5	4		3		2	3
Fabricated metal products	47	4	15	10	21	1	25	6	6	4
Machinery and equipment			12	5	2		3	2	14	6
Electronics (31 & 32)	3		3	4	6	1	3	1	5	2
Precision instruments										1
Transport machines (34&35)	1	1	14	10	2		2		10	6
Furniture	21	6	41	14	56	16	20	11	6	2
Recycling	1	1						1		

Table C.3: Input-essential innovation by country and two-digit sector

	Country and Did the firm introduce a product innovation for which new inputs were essential?									
	Ghana		Bangladesh		Tanzania		Uganda		Kenya	
Industry	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Food	39	1	85	13	43	2	41	6	98	7
Textiles	2		57	38	21		22	3	15	1
Garments	15	2	74	21	39	1	7	1		
Leather	2		72	17			1		4	
Wood	13		9	3	15		4	2	4	
Paper	2	1	18	5			1		1	
Publishing, printing, and Recorded media	40	1	39	10	12		4		7	
Refined petroleum product	3								3	
Chemicals	12	1	53	12	7		2		16	2
Plastics & rubber	12	3	18	7	7		2	1	2	2
Non metallic mineral products	13	1	10	1	8		4		5	1
Basic metals	6		18	3	4		1		2	1
Fabricated metal products	47		11	6	20	2	19	1	7	1
Machinery and equipment			9		2		4		13	3
Electronics (31 & 32)	3		4	2	6	1	3	1	5	
Transport machines (34&35)			19		2		1		11	
Furniture	17	3	32	8	58	6	17	2	6	
Recycling	1									

Appendix D Main import trading partners

Table D.1 reports the list of main import partners in terms of total import values and Table D.2 reports the list in terms of number of varieties. In both cases, China's position has increased from 2005 to the top 3 in 2010 in all sample countries.

Table D.1: Top 5 import countries measured by share of value of imports

	2005			2010	
Position	**Country of origin**	**Share**	**Position**	**Country of origin**	**Share**
			Bangladesh		
1	**China**	0.16	1	**China**	0.17
2	India	0.11	2	India	0.12
3	Kuwait	0.07	3	Thailand	0.06
4	Japan	0.06	4	Singapore	0.05
5	Rep. of Korea	0.05	5	China, Hong Kong SAR	0.05
			Ghana		
1	Nigeria	0.12	1	USA	0.14
2	**China**	0.08	2	**China**	0.13
3	United Kingdom	0.08	3	France	0.06
4	USA	0.07	4	Belgium	0.06
5	Belgium	0.06	5	United Kingdom	0.05
			Kenya		
1	United Arab Emirates	0.14	1	**China**	0.13
2	South Africa	0.10	2	United Arab Emirates	0.12
3	USA	0.10	3	India	0.11
4	Saudi Arabia	0.06	4	South Africa	0.06
5	United Kingdom	0.06	5	Japan	0.06
			Uganda		
1	Kenya	0.25	1	India	0.15
2	Japan	0.07	2	Kenya	0.11
3	South Africa	0.07	3	**China**	0.09
4	United Arab Emirates	0.07	4	United Arab Emirates	0.08
5	India	0.06	5	Japan	0.07
			Tanzania		
1	Bahrain	0.16	1	India	0.11
2	South Africa	0.12	2	**China**	0.11
3	**China**	0.07	3	South Africa	0.10
4	Japan	0.06	4	United Arab Emirates	0.08
5	United Arab Emirates	0.06	5	Japan	0.07

Table D.2: Top 5 import countries measured by share of number of varieties

	2005			2010	
Position	**Country of origin**	**Share**	**Position**	**Country of origin**	**Share**
			Bangladesh		
1	**China**	0.21	1	**China**	0.21
2	India	0.17	2	India	0.17
3	Singapore	0.06	3	China, Hong Kong SAR	0.08
4	Other Asia, nes	0.06	4	Singapore	0.08
5	Rep. of Korea	0.05	5	Other Asia, nes	0.06
			Ghana		
1	United Kingdom	0.13	1	United Kingdom	0.12
2	**China**	0.09	2	**China**	0.12
3	Germany	0.08	3	USA	0.10
4	South Africa	0.08	4	South Africa	0.09
5	USA	0.08	5	India	0.07
			Kenya		
1	India	0.14	1	**China**	0.15
2	United Kingdom	0.14	2	India	0.14
3	**China**	0.11	3	United Kingdom	0.11
4	South Africa	0.10	4	South Africa	0.08
5	United Arab Emirates	0.09	5	USA	0.07
			Uganda		
1	United Arab Emirates	0.19	1	**China**	0.16
2	Kenya	0.18	2	United Arab Emirates	0.15
3	South Africa	0.13	3	Kenya	0.14
4	India	0.11	4	India	0.13
5	United Kingdom	0.11	5	South Africa	0.09
			Tanzania		
1	South Africa	0.15	1	**China**	0.14
2	United Arab Emirates	0.13	2	South Africa	0.13
3	**China**	0.12	3	United Arab Emirates	0.13
4	India	0.11	4	India	0.11
5	United Kingdom	0.08	5	United Kingdom	0.07

Appendix E Gravity model of relative exports

We adapt the method Autor et al. (2013) to estimate the Chinese export-supply capability over time for different products. Starting from a basic gravity model of trade, China's (CH) exports to country c in industry j, relative to the United States (US) are given by the following equation:

$$\ln\left(\frac{X_{CHjc}}{X_{USjc}}\right) = \ln\left(\frac{z_{CHj}}{z_{USj}}\right) + \left[-\left(\sigma_j - 1\right)\ln\left(\frac{\tau_{CHjc}}{\tau_{USjc}}\right)\right], \tag{9}$$

where $\ln\left(\frac{z_{CHj}}{z_{USj}}\right)$ is China's comparative advantage in industry j relative to the US and $\ln\left(\frac{\tau_{CHjc}}{\tau_{USjc}}\right)$ captures Chinese trade cost relative to the US for exports of industry j's goods to country c. By taking relative exports, demand-side factors in the importing country c are removed, leaving only differences in comparative advantage (productivity) and trade costs.

We estimate the following regression equation,

$$\ln\left(\frac{X_{CHjc}}{X_{USjc}}\right) = \alpha_j + \alpha_c + \varepsilon_{jct}, \tag{10}$$

where t indexes a year, α_j is the industry fixed effects (China's mean comparative advantage vis-à-vis the U.S.) and α_c is the imported fixed effect (the time-invariant difference in trade costs, driven by geography). Subtracting Equation (10) from Equation (9) (with a time-dimension) and rearranging gives the following expression for the residual:

$$\varepsilon_{jct} = \ln\left(\frac{z_{CHjt}}{z_{USjt}} - \alpha j\right) + \left[-\left(\sigma_j - 1\right)\ln\left(\frac{\tau_{CHjct}}{\tau_{USjct}}\right) - \alpha_c\right], \tag{11}$$

The residual, ε_{jct}, is thus the sum of China's demeaned comparative advantage in industry j and trade-costs in industry j to country c in year t relative to the U.S. We estimate $\widehat{\varepsilon_{jct}}$ from Equation (10) and sum over destination countries c to obtain $\overline{\varepsilon_{jt}}$. Therefore, captures exogenous variation in China's export-supply capabilities across industries j and countries c.

Appendix F Robustness

F.1 Different years

Table F.1: Robustness - different years: innovation and new input innovation

	Innovation				New input innovation			
Log new input varieties 2008	0.33***				0.54***			
	(0.12)				(0.16)			
Log new input varieties 2009		0.26				0.54**		
		(0.20)				(0.25)		
Log new input varieties 2009			0.35**				0.54***	
w.r.t 2007			(0.14)				(0.20)	
Log new input varieties 2010				0.11				0.50**
				(0.21)				(0.25)
N	1837	1837	1837	1837	1830	1830	1830	1830

The table reports OLS regressions of innovation (innovation or new input innovation) between 2009-2012 on log new input varieties in different year. All regressions include country dummies, four-digit industry dummies, three size dummies, dummies for government and foreign ownership and age. Robust standard errors (clustered by 4digit-industry-country) are reported in parentheses. Significance: *10%, **5%, ***1%.

Table F.2: Robustness - different years: input-essential innovation and input non-essential innovation

	Input-essential innovation				Input non-essential innovation			
Log new input varieties 2008	0.45***				-0.014			
	(0.091)				(0.12)			
Log new input varieties 2009		0.58***				-0.25		
		(0.14)				(0.18)		
Log new input varieties 2009			0.52***				-0.051	
w.r.t 2007			(0.11)				(0.14)	
Log new input varieties 2010				0.49***				-0.24
				(0.15)				(0.17)
N	1485	1485	1485	1485	1485	1485	1485	1485

The table reports OLS regressions of innovation (input-essential innovation or input non-essential innovation) between 2009-2012 on log new input varieties in different year. All regressions include country dummies, four-digit industry dummies, three size dummies, dummies for government and foreign ownership and age. Robust standard errors (clustered by 4digit-industry-country) are reported in parentheses. Significance: *10%, **5%, ***1%.

F.2 Probit

Note that the OLS samples (as reported in Section 5) are generally larger than the sample size reported below, because some 4-digit industry dummies predict failure (no innovation) perfectly. When the dependent variable (innovation) does not vary within one of the categories of one or more independent variable (in this case a number of industry dummies), maximum likelihood estimation is not possible. When in at least one industry all firms did (not) innovate, the model can not be fitted as the coefficient on that industry is positive (negative) infinity. The only way the model can be fitted, is if the observations in this industry are dropped from the regression sample[17].

Table F.3: Robustness - Probit: product innovation between 2009-2012

	Innovation Innovation		New input innovation		Input-essential innovation	
	(1)	(2)	(3)	(4)	(5)	(6)
Log new input varieties 2009	0.35	0.38	0.57^{**}	0.47	0.55^{***}	0.41^{**}
	(0.24)	(0.33)	(0.28)	(0.35)	(0.15)	(0.19)
Log new output varieties 2009		0.0084		0.049		0.055
		(0.071)		(0.073)		(0.042)
N	1779	1752	1740	1715	1322	1302

The table reports probit regressions of innovation (innovation, new input innovation or input-essential innovation) between 2009-2012 on log new input varieties in 2009. All regressions include country dummies, four-digit industry dummies, three size dummies, dummies for government and foreign ownership and age. Robust standard errors (clustered by 4digit-industry-country) are reported in parentheses. Significance: *10%, **5%, ***1%.

Table F.4: Robustness - Probit: product innovation between 2009-2012

	Innovation Innovation		New input innovation		Input-essential innovation	
	(1)	(2)	(3)	(4)	(5)	(6)
Log new input varieties 2009	0.068	-0.022	0.28	0.035	0.39^{**}	0.20
	(0.22)	(0.26)	(0.26)	(0.27)	(0.15)	(0.18)
Log new output varieties 2009		0.064		0.11		0.084^{**}
		(0.065)		(0.070)		(0.042)
N	1779	1752	1740	1715	1322	1302

The table reports probit regressions of innovation (innovation, new input innovation or input-essential innovation) between 2009-2012 on new input varieties in 2009 and log new output, where the independent variables are weighted by HS products. All regressions include country dummies, four-digit industry dummies, three size dummies, dummies for government and foreign ownership and age. Robust standard errors (clustered by 4digit-industry-country) are reported in parentheses. Significance: *10%, **5%, ***1%.

F.3 Subsamples

Tables F.5 below is the equivalent of Tables 4 in Section 4, with the regressions run on the subsample of input-essential innovation.

[17]The numbers depends on the dependent variable, but as an indication, in column (1) of Table 4, 58 firms in 29 of of the 102 4digit-industries are excluded. These industries have an average of 2 firms in our sample; with a maximum of 6.

Table F.5: Robustness - Subsample: product innovation between 2009-2012

	Innovation Innovation		New input innovation		Input-essential innovation	
	(1)	(2)	(3)	(4)	(5)	(6)
Log new input varieties 2009	0.33^{*}	0.36	0.58^{***}	0.49^{**}	0.58^{***}	0.49^{***}
	(0.19)	(0.22)	(0.17)	(0.19)	(0.14)	(0.15)
Log new output varieties 2009		-0.012		0.044		0.040
		(0.049)		(0.036)		(0.030)
N	1485	1461	1485	1461	1485	1461

The table reports OLS regressions of innovation (new input or new input innovation) between 2009-2012 on log new input varieties in 2009 on sub-sample for which the input-essential innovation variable is not missing. All regressions include country dummies, four-digit industry dummies, three size dummies, dummies for government and foreign ownership and age. Robust standard errors (clustered by 4digit-industry-country) are reported in parentheses. Significance: *10%, **5%, ***1%.

F.4 Instrumental variables

Table F.6: Robustness - IV estimation with customs delay as instrument

	two-digit industry customs delay			sub-sample non-importing firms		
	Innovation	New input innovation	Input-essential innovation	Innovation	New input innovation	Input-essential innovation
Panel A: Second stage						
Log new input varieties 2009	0.42	2.52**	1.11	0.49	1.62**	0.60
	(1.05)	(1.26)	(0.89)	(0.84)	(0.74)	(0.45)
Panel B: First stage Input Varieties						
Log customs delay 2-digit	-0.018*	-0.018*	-0.017			
	(0.011)	(0.011)	(0.011)			
Log customs delay				-0.031***	-0.031***	-0.029***
				(0.011)	(0.011)	(0.011)
N	1697	1691	1373	1000	997	825
F-stat	2.96	2.95	2.52	8.07	8.06	7.17

The table reports IV regressions of innovation (innovation, new input innovation or input-essential innovation) between 2009-2012 on log new input varieties in 2009. In columns 1-3, the instrument is log new input varieties in the same industry in a similar country (see Section 4.4 for the similar countries) measured at the two-digit industry-country level. In columns 4-5 customs delay is measured at the four-digit industry-country level, but the regression is run on a sub-sample of non-importing firms. All regressions include country dummies, four-digit industry dummies, three size dummies, dummies for government and foreign ownership and age. Robust standard errors (clustered by 4digit-industry-country) are reported in parentheses. Significance: *10%, **5%, ***1%.